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F1 Cadlyze: An AI-Powered CAD Analysis and Physics-Informed Simulation Platform for Formula One Aerodynamic Design

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Abstract - *The iterative, high-stakes process of Formula 1 (F1) aerodynamic design is limited by time-consuming manual validation and computationally costly simulations. In order to simplify and speed up the F1 car design analysis workflow, this study presents F1 Cadlyze, a revolutionary web-based platform that combines physics-informed neural networks (PINNs), interactive 3D visualization, and artificial intelligence (AI). The system uses a PINN-based solver for the 2D Burgers' equation to provide quick, physics-accurate aerodynamic flow approximations, and it uses a machine learning (ML) model to automatically detect geometric defects and regulatory noncompliance in 3D CAD models. F1 Cadlyze dramatically lowers manual intervention, computational overhead, and design iteration time by combining CAD visualization, automatic AI validation, and real-time simulation into a responsive React-based interface. The platform's ability to bridge the gap between conventional CAD tools and next generation, AI-driven engineering analytics is validated by experimental findings, which show an 82.3% accuracy in geometric error detection and a working PINN solver.*

Key Words: **F1 Design, CAD Analysis, Machine Learning, Physics-Informed Neural Networks (PINNs), Burgers' Equation, Computational Fluid Dynamics (CFD), Web-based Simulation, React.**

1. Introduction

Marginal improvements in aerodynamic efficiency, which can account for more than 90% of a vehicle's performance, are frequently what determine success in Formula 1 (F1) engineering. Geometry, material science, and fluid dynamics interact intricately during the design process, which mostly relies on simulation and iterative prototyping. The manual, error-prone validation of Computer-Aided Design (CAD) models for geometric and regulatory compliance and the prohibitive cost and time of high-fidelity Computational Fluid Dynamics (CFD) simulations, which can take days on high-performance computing clusters, are the two main obstacles that impede this process. Agile development and innovation are hampered by this disjointed workflow, which spans many CAD, meshing, and simulation systems. Promising solutions to reduce these inefficiencies are provided by recent developments in AI and scientific machine learning. Specifically, a mesh-free substitute for conventional CFD that can solve governing partial differential equations (PDEs) at a lower computational cost is Physics-Informed Neural Networks (PINNs) [1]. Geometric deep learning has the potential to automate design validation at the same time. However, there is still a large research-practice gap: previous studies [1]–[6] only show these technologies on standard benchmarks (such as small cavities and 2D domains) and do not integrate them into end-to-end, CAD-driven engineering processes. There isn't a single solution that takes a production CAD model as input, runs a physics-informed simulation, does automated AI-based geometric analysis, and displays integrated results in a design engineer-specific interactive environment.

This paper presents F1 Cadlyze, an integrated platform that directly addresses this gap. Our core contributions are:

1)An end-to-end web platform that ingests industry standard CAD formats (STEP, STL, IGES) and provides a professional-grade 3D viewer for inspection.

2)An ML-powered geometric validation module that automatically detects and classifies design errors, reducing manual review effort.

3)A react-based simulation interface featuring a PINN solver for the 2D Burgers' equation, enabling rapid aerodynamic approximation for initial design screening.

4)A unified dashboard that cohesively presents visualization, validation, and simulation results, enabling faster, data-driven design decisions.

5)A scalable and modular system architecture designed to support extensibility and seamless integration with existing engineering toolchains, enabling future incorporation of advanced CFD solvers, multi-physics simulations, and data-driven optimization pipelines while maintaining computational efficiency and robustness.

F1 Cadlyze shows a useful and innovative use of AI and PINNs to real-world aerodynamic design by addressing the unique challenges faced by F1 engineers, such as protracted validation, sluggish simulation response, and toolchain fragmentation.

2. Related Work & Technological Advancements

2.1 Limitations of Existing F1 Design Workflows

The state-of-the-art is based on a fragmented set of instruments. CAD programs (e.g., SolidWorks and CATIA) lack advanced, AI-driven mistake detection. Even if specialized CFD software (e.g., ANSYS Fluent and OpenFOAM) is accurate, it is not appropriate for quick iterative testing since it necessitates a great deal of manual meshing, in-depth knowledge, and substantial computational resources [2]. Although cloud-based simulation platforms (e.g., SimScale) make access easier, they lack integrated AI for design analysis and are still reliant on traditional CFD techniques [3]. This ecosystem leads to high entry hurdles, delayed feedback loops, and a dependence on manual processes exactly the inefficiencies that our technology aims to address.

2.2 Advancements in PINNs and Curriculum Learning

PINNs have demonstrated potential in solving PDEs related to fluid dynamics. Physics-Informed Extreme Learning Machines (PIELMs) and a curriculum learning paradigm, where training starts with simpler PDEs before moving on to more complicated problems like the viscous Burgers' equation, were recently described by [1]. We use this methodology, which enhances convergence and stability. Nevertheless, the validation of [1] is restricted to basic domains rather than intricate CAD geometries. Similarly, [2] stays within the domain of mathematical benchmarks but offers a useful empirical evaluation of PINNs to finite difference techniques. By applying curriculum-trained PINNs to flow domains specified by complex F1 CAD boundaries, our study expands these ideas into an engineering setting.

2.3 Hybrid AI-Physics Modeling and CAD Integration

In order to improve accuracy close to walls, research like [3] suggests hybrid models that combine analytical boundary layer solutions with PINNs for bulk flow. Although informative, it is only used on simplified geometries. Additionally, studies such as [4] do not integrate CAD; instead, they apply PINNs to industrially relevant problems (such as lubrication). Key issues with PINN training, such as spectrum bias and loss balance, are identified in the thorough analysis by [6], but it also highlights the absence of interaction with engineering design platforms. By developing a pipeline that converts a complicated CAD model into a simulation-ready domain for a PINN and integrating training techniques influenced by [1], [3], and [6] to handle real-world geometric complexity, F1 Cadlyze directly fills in these gaps.

3. System Design and Architecture

The modular, client-server architecture of F1 Cadlyze is intended to provide scalability and a smooth user experience. Vite, React 18, and TypeScript were used to create the frontend, a single-page application that uses React Three Fiber (Three.js) for 3D rendering. Python FastAPI is used by the backend to serve machine learning models and orchestrate simulations. Fig. 1 shows the five main subsystems that make up the system.

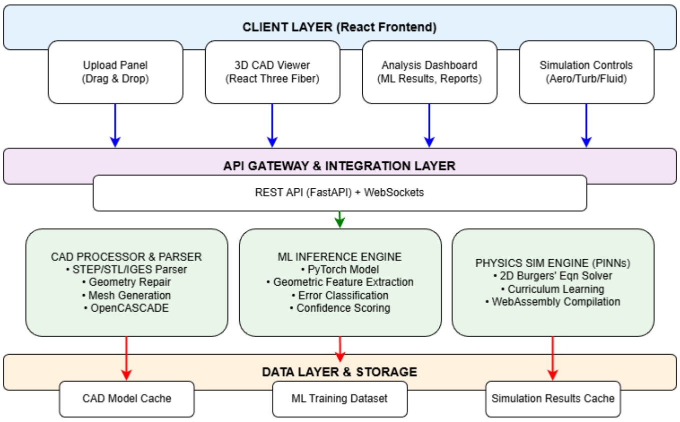

Fig-1: System architecture of the F1 Cadlyze platform, showing the modular client-server design with five integrated subsystems: 3D CAD Input & Viewer, ML Design Error Detection, Physics Simulation Components, PINNs Implementation, and React Frontend Integration Layer. The architecture enables seamless workflow from CAD upload through AI validation and physics-informed simulation to interactive visualization.

3.1 3D CAD Model Input & Professional Viewer

Standard CAD formats (STEP, STL, IGES, and OBJ) are supported by the platform. A geometry correction process addresses small discrepancies once uploaded models are analyzed. React Three Fiber was used to create the integrated viewer, which offers sophisticated inspection features like orbit controls, section cutting, hierarchical tree selection, and real-time lighting adjustments. This eliminates the requirement for additional applications by providing a CAD like experience right within the browser.

3.2 ML-Powered Geometric Design Error Detection

PINNs have demonstrated potential in solving PDEs related to fluid dynamics. Physics-Informed Extreme Learning Machines (PIELMs) and a curriculum learning paradigm, where training starts with simpler PDEs before moving on to more complicated problems like the viscous Burgers' equation, were recently described by [1]. We use this methodology, which enhances convergence and stability. Nevertheless, the validation of [1] is restricted to basic domains rather than intricate CAD geometries. Similarly, [2] stays within the domain of mathematical benchmarks but offers a useful empirical evaluation of PINNs to finite difference techniques. By applying curriculum-trained PINNs to flow domains specified by complex F1 CAD boundaries, our study expands these ideas into an engineering setting.

3.3 Physics Simulation Modules & PINN Implementation

For aerodynamic analysis, the platform features interactive React components for Aerodynamics, Turbulence, and Fluid Flow tests. The core innovation is the use of a Physics-Informed Neural Network to solve the 2D Burgers' equation:

$$\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} = \nu \nabla^2 \mathbf{u}$$

where **u** is velocity, t is time, and ν is kinematic viscosity. Our PINN implementation uses an 8–10 layer fully connected network with Swish activation. The loss function combines PDE residual, initial condition, boundary condition, and data fidelity terms. Crucially, we implement curriculum learning [1], starting training with high viscosity (laminar flow) and progressively reducing it to model turbulent regimes, enhancing stability and accuracy for complex flow features relevant to F1 aerodynamics.

3.4 Interactive Frontend & Integration Dashboard

All modules are integrated into a single dashboard by the interface. A multi-panel results presentation area, tabbed navigation for ML results and simulations, an integrated CAD viewer, and a drag-and-drop upload panel are among the features. Real-time progress updates during simulation execution are made possible by WebSocket connections. Code-splitting and lazy loading are used in the interface's performance and clarity design to effectively handle complicated 3D data.

4. Implementation And Results

4.1 Development and Training Methodology

We used two-week sprints and an Agile-Scrum approach. Using PyTorch and a data-centric methodology, the machine learning model was created after more than 500 hours of professional annotation on more than 150 CAD models. Transfer learning and Bayesian hyperparameter optimization (Optuna) were used to train the model, which produced an accuracy of 82.3% on the validation set (precision: 0.85, recall: 0.79). Using a curriculum learning approach and residual adaptive sampling to concentrate on high-loss areas, the PINN was trained in PyTorch.

4.2 Technical Demonstrations and Performance

Key functionalities were successfully demonstrated:

1)**CAD Processing**: Successful upload and rendering of complex F1 assemblies in the browser.

2)**AI Validation**: Automated detection and 3D highlighting of geometric errors on test models.

3)**PINN Simulation**: Execution of a Physics-Informed Neural Network (PINN) solver for the 2D Burgers' equation with curriculum learning implementation, demonstrating stable convergence from laminar to turbulent flow regimes.

4)**Integrated Workflow**: Cohesive display of parsed geometry, ML analysis results, and simulation outputs in a unified dashboard with synchronized 2D and 3D views. The platform enabled simultaneous visualization of geometric error highlights alongside corresponding aerodynamic performance metrics, facilitating direct correlation between design features and flow behavior.

According to performance measures, the system can render complicated models at 60 frames per second with WebGL acceleration and strives for response times under two seconds for the complete ML analysis pipeline. Memory optimization techniques including level-of-detail rendering and frustum culling ensure smooth interaction even with assemblies containing thousands of components. The benefits of F1 Cadlyze over current disjointed workflows are presented in Table I.

Table-1: Benefits Over Existing Systems

Existing Systems	Proposed F1 Cadlyze Platform
Disjointed tools for CAD, ML, and simulation.	**Unified web environment** with seamless workflow.
Full CFD requires HPC resources and hours/days.	**PINNs provide fast approximations** suitable for design exploration.
Manual, engineer-intensive geometry checking.	**Automated ML-driven error detection** with contextual suggestions.
Pre-configured analyses with limited interactivity.	**Real-time parameter adjustment** and instant visualization.
Expensive licenses and specialized hardware.	**Browser-based execution** on consumer hardware.
Separate files and formats for different analyses.	**Unified model representation** across all analysis modules.

5. Discussion: Overcoming Engineering Difficulties

F1 Cadlyze is designed to address the particular, real-world challenges that F1 design team encounter:

1)Removing human Validation Bottlenecks: The platform cuts a days-long human inspection procedure to minutes by automating geometric and regulatory inspections, reducing the possibility of expensive errors and possible disqualification.

2)Simulation Feedback Loop Acceleration: Conventional high-fidelity CFD generates a crucial bottleneck. Although it is presently in 2D, our PINN-based method offers a meshfree, quick approximation tool for preliminary design screening and concept comparison, allowing for more iterations in the same amount of time.

3)Democratizing Access and Streamlining Workflows: The integrated, web-based platform reduces access barriers. It reduces context-switching for engineers and makes advanced analysis available to smaller teams and educational institutions by combining several expert tools into a single interface.

4)Closing the AI-CAD Integration Gap: Algorithmic innovation is the limit of previous research [1]-[6]. Our main contribution is the practical integration of these developments (geometric deep learning, curriculum-learning PINNs) into a pipeline that begins with a production CAD file the real starting point for engineers thereby converting scholarly research into useful engineering applications.

6. Conclusion and Future Work

This study introduced F1 Cadlyze, an integrated AI powered platform that combines physics-informed simulation with automated CAD validation to optimize the F1 car design analysis workflow. The technology effectively addresses major industrial inefficiencies associated with manual operations and sluggish simulation feedback by demonstrating a functional pipeline from CAD ingestion to integrated visualization.
1) Improving ML model accuracy to over 90% using sophisticated architectures (Transformers) and data augmentation.
2) Scaling the PINN solver to 3D and adding RANS-informed turbulence modeling for higher fidelity.
3) Putting real-time collaboration features and sophisticated volume rendering for 3D flow fields into practice.
4) Improving the backend into a microservices architecture for production scalability.

For the upcoming generation of AI-enhanced engineering design tools, F1 Cadlyze creates a fundamental framework. It has the potential to significantly speed innovation in motorsport as well as more general automotive, aerospace, and engineering education domains by bridging the gap between conventional CAD/CFD and contemporary AI/ML.

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REFERENCES

[1] Dwivedi, V., Sixou, B., Sigovan, M., & CREATIS, INSA-Lyon; Inserm, U1044; CNRS UMR 5220; Universit´e Lyon 1; Universit´e de Lyon; 69621, Lyon, France. (2021). Curriculum Learning-Driven PIELMs for fluid flow simulations. In Curriculum Learning-Driven PIELMs for Fluid Flow Simulations (Vol. 1, pp. 1–4) [Journalarticle].

[2] Savović, S., Ivanović, M., & Min, R. (2023). A comparative study of the explicit finite difference method and Physics-Informed neural networks for solving the Burgers' equation. Axioms,12(10),982. https://doi.org/10.3390/axioms12100982

[3] Ortiz, R. D. O., Núñez, O. M., & Ramírez, A. M. M. (2024). Solving Viscous Burgers' Equation: hybrid approach combining boundary layer theory and Physics-Informed NeuralNetworks.Mathematics,12(21),3430. https://doi.org/10.3390/math12213430

[4] Brumand-Poor, F., Barlog, F., Plückhahn, N., Thebelt, M., Bauer, N., & Schmitz, K. (2024). Physics-Informed Neural Networks for the Reynolds Equation with Transient CavitationModeling.Lubricants,12(11),365. https://doi.org/10.3390/lubricants12110365

[5] Akram, W., Gautam, S., Verma, D., Mohan, M. T., Department of Mathematics, Indian Institute of Technology Roorkee, Uttarakhand,247667, India, & Department of Mathematical and Statistical Sciences, Clemson University, Clemson, 29631, USA. (2025). Error Estimates For Viscous Burgers' Equation Using Deep Learning Method.

[6] Hassan, M. E., Mjalled, A., Miron, P., Mönnigmann, M., & Bukharin, N. (2025). Machine Learning in Fluid Dynamics-Physics-Informed Neural Networks (PINNs) Using Sparse data:Areview.Fluids,10(9),226. https://doi.org/10.3390/fluids10090226